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Demand side management using artificial neural networks in a smart grid environment

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ABSTRACT

Smart grid deployment is a global trend, creating endless possibilities for the use of data generated by dynamic networks. The challenge is the transformation of this large volume of data into useful information for the electrical system. An example of this is the application of demand side management (DSM) techniques for the optimisation of power system management in real time. This article discusses the use of DSM in this new environment of electrical system and it presents a simulation that uses data acquired from digital meters, it creates patterns of load curves, uses these patterns load data to train and validate a ANN and uses this ANN to classify new data using these defined patters. The results obtained in this study show that the intelligent network environment facilitates the implementation of DSM and the use of ANN presented a satisfactory performance for the classification of load curves.

Contents

1. Introduction

The increased complexity of electric power systems in recent years has contributed significantly to the quest for efficient management, which requires a deeper knowledge of the whole electric system through the implementation of digital technology systems [1]. These systems can provide information to improve the management of electrical systems, monitor the type of consumption, and track all events and contingencies of energy networks.

Smart grids are based on the integrated use of information technology, telecommunications, automation, and control of the electricity network, involving smart meters, sensors, and digital network management devices, and are bi-directional, allowing the deployment of control strategies and optimisation of the electric network, with real-time data processing [2–4].

This convergence of technologies offers a volume of highly reliable data, including data at points of consumption and evaluations of voltage, current, and power loss. It allows the power source to be controlled with more autonomy for the consumer units and enables energy management to be implemented in a more decentralised manner, requiring the development of new control and optimisation methods for the operation of an electrical system [5].

In addition, there are many possible new services that may be offered from multiple features, such as differentiated charging,

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dynamic pricing and direct control load, enabling the use of demand side management (DSM) to optimise electrical system planning and management [6–8].

The availability of data from digital power meters for consumers provides a more decentralised control of electricity consumption. This smart grid feature is of great importance because the consumer can play a more active role in the management of energy; this consumer empowerment to gain control of energy consumption allows consumers to supply any surplus energy back to the electric network in a distributed generation system [9].

The challenge is the transformation of this large volume of data into relevant information to manage the electrical system. The processing of these data using tools such as statistical methods, artificial neural networks, and data mining techniques provides greater knowledge of the consumption habits and contributes to the implementation of power management policies, which are most appropriate for each case, such as the classification of load profile for use in DSM [10].

This article discusses the use of the DSM techniques in the smart grid environment and presents a simulation of a data classifier generated by digital meters using an artificial neural network (ANN) to classify the load curve patterns to choose the most suitable DSM policies for each type of consumer ranked over the network. Section 2 of this article presents the characteristics, most commonly used policies, and concepts associated with DSM. Section 3 presents the basic concepts associated with the ANN used in the simulation. Section 4 describes the simulation procedure and results. Finally, closing remarks are presented in Section 5.

2. Demand side management (DSM)

There are basically two forms of action for energy management: supply side management, which involves the construction of new generating units and the control of demand using energy conservation policies, and demand side management (DSM), which involves the reduction of waste and the use of more efficient equipment [9].

Most researchers define DSM as a program or set of activities organised by the utility that affect the amount and timing of consumer use. DSM is a means to intervene in the use and the variety of modes of energy consumption [10–14].

One of the goals of DSM is to reduce the peak. DSM aims to reduce the peak the levels of energy demand throughout the day; DSM is a set of policies essentially aimed at the economic return on investment made and/or postponement of new facilities, acting mostly on the compatibility of the load factor of the region with energy. DSM involves controlling the consumer side loads to operate the system more efficiently, which implies obtaining a load factor (the relationship between the average demand and maximum demand) [14–16].

A DSM program implements technologies or activities that might change the way customers consume to incentivise consumers to change their times of use to avoid maximum load. This is only feasible with the installation of smart meters for every consumer, which provide detailed and differentiated rate measurements over time and inform the consumer about their consumption and quality indicators [14–18].

The success of DSM is to provide consumers with a better energy service at a lower cost, reducing the duration of blackouts, faults, and defects [18–20]. The general steps of the program are

- Data acquisition.
- Analysis of system load characteristics.
- Market study and growth prospects in the short and long terms.
- Investigation of various forms of energy supply and the costs involved.
- Definition of appropriate modelling system loads for the study.
- Consumer awareness, encouragement of consumer participation, and analysis of the general costs of and evolution of the program, growing autonomously and with modifications.

One of the main elements of an effective energy management program is the characterisation of the charge, which consists of three steps: data collection, load analysis, and demand projection.

Data collection involves a set of actions, methods, and routines that acquire data. The quality and reliability of the data collected is a key factor in the base studies and planning of the electrical system.

Load analysis involves tracking the registration of each consumer to characterise the type of load and to choose which tools are more suitable for a set of loads with similar characteristics. The demand, type of load (connection), market expansion, and other aspects of the existing load are analysed.

The projection of demand occurs after the data analysis and is important for predicting the growth rate and planning the system.

The acquisition of daily load curve data for all consumers in an electric system is technically impossible or nearly impossible without the aid of new technologies because conventional energy meters do not record this information. Therefore, in this case, the curve is acquired periodically every four or five years by sampling a small portion of the population.

A randomly chosen sample usually represents only a small part of the population of interest. The information thus obtained is then extrapolated to the population. The main issue is whether the behaviour of the sample can be transferred to the population without deformation, ensuring that the representativeness and accuracy of the data obtained reflect a static situation obtained every four years.

The use of a smart grid changes this situation significantly by allowing access to the daily load curve data for each consumer in real time and the use of appropriate tools to extract information about consumer habits.

After the curves of consumer characteristics are determined, they can be grouped for analysis of the secondary system and transformers. The load information for the transformers is then used for the primary system planning and for the analysis of the substations. The system loads determine the type, power, and installation location of the substation.

The most frequently used DSM techniques [10–16], shown in Fig. 1, are peak reduction techniques, filling valleys, moving tips, conservation strategy, strategic growth, and flexible modelling techniques.

(a) Peak clipping: load cutting, demand reduction in time for a heavy load. The duration of the peak can be reduced by direct load control, shutdown of consumer equipment, or distributed generation.
(b) Valley filling: encourages off-peak consumption. Non-peak consumption periods are increased, which is particularly desirable because the cost of production is lower, decreasing the average price and improving the efficiency of the system. Various incentives, such as discounts, motivate certain consumers to change their habits.
(c) Strategic conservation: reduces seasonal energy consumption mainly by increasing consumption efficiency and reducing energy waste. This program is quite comprehensive and includes incentives for technological change.
(d) Strategic load growth: controls the increase seasonal energy consumption. The dealership employs intelligent systems and processes, more efficient equipment, and more competitive energy sources to achieve their goals.
(e) Load shifting: shifts the workload transfer period of greatest consumption (peak period to period of lower consumption)

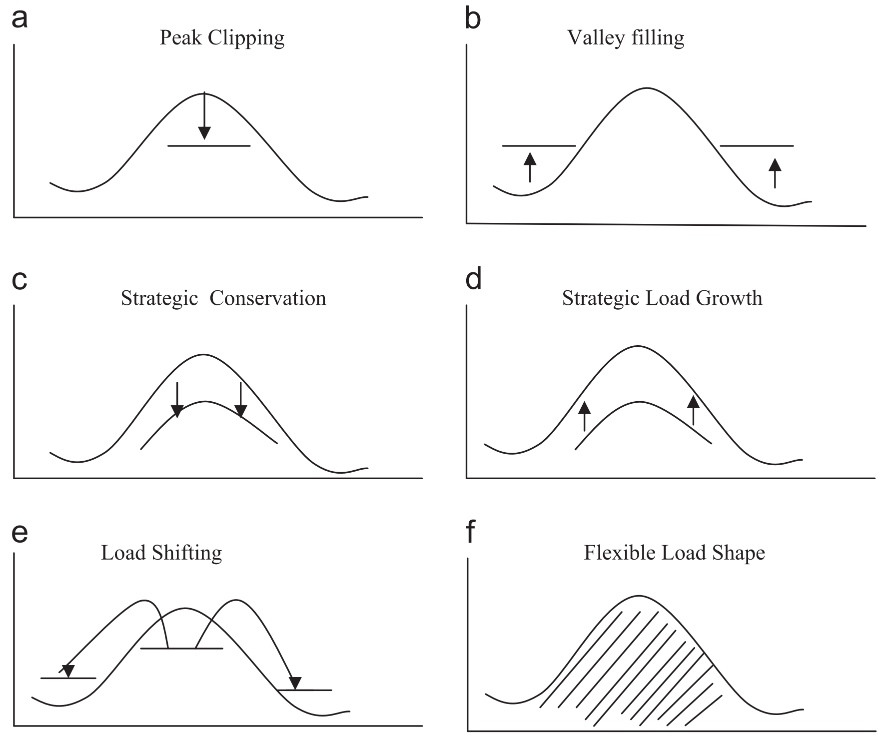

Fig. 1. DSM techniques.

and moves tip out loads without changing the total consumption. This is also possible with distributed generation.

(f) Flexible load shape: a set of actions and integrated planning between the concessionary and the consumer, subject to the needs of the moment. This approach models consumer loads without affecting the actual security conditions, limiting the power and energy that the individual consumer can use at certain times by installing load-limiting devices.

This system involves a huge volume of data that must be processed to maintain a knowledge base about the various features of the system. The success of the management program is directly linked to 24-hour-a-day monitoring; thus, the behaviour of each type of load is determined, including the typical and non-typical days for each load, and used to take precise actions for each case [12–16]. However, this achievement requires management to classify the various types of loads that reflect the type of consumption.

There are several techniques for classifying a large volume of data, including data mining [17]; statistical techniques, such as dynamic clouds; or artificial intelligence, such as in artificial neural networks (ANNs). ANN was chosen due to its robustness characteristics, its adaptive capacity in the face of a very large volume of data in real time, and other features described below.

3. Artificial neural networks (ANN)

The concept of artificial neural networks (ANNs) is associated with a signal processing system and information consisting of a large number of simple processors, called neurons or cells, that emulate biological nervous systems in programs or digital circuits. These neurons are interconnected by direct connections, called synapses, which allow distributed parallel processing, and their main feature is their adaptive capacity, i.e., their ability to learn and establish precise, complex relationships between various numeric variables without any preconceived model being imposed [21–25].

ANNs are often applied in systems where no mathematical model is available or accurate enough to represent the phenomenon. Each ANN layer, can be described by expression (1):

$$Y_j=\psi\left(\sum_{i=0}^{n} W_{ji}X\_i+\theta\_j\right) \tag{1}$$

where W_{ji} is the synapse weight, θ_j is a constant, X_j is the input vector, Y_j is the output vector, and ψ is the activation function.

The term activation function is used to refer to the function ψ that converts the input value to an output value of a network node. The most commonly used activation functions are sigmoid function, step function, linear function, sign function and hyperbolic tangent function [21–27].

Fig. 2 shows a implementation of a ANN with N inputs. The signals of a given neuron are the state or value of the activation of neurons, which are multiplied by a corresponding weight W_i. The state of the neuron is calculated by applying a threshold function (activation) ψ_n when the given input value to the neuron, i.e., the sum of the values of the activation of neuron precedents, are multiplied by their weights as shown in Eq. (1).

For an ANN can provide convenient results, it is necessary to pass through a phase of training, where their weights are adjusted so that it adapts to the different inputs. The ANN learning occurs during this phase of training [25–27].

The training algorithm to define the weights that shape the system must have an error nearly zero, i.e., The goal of the ANN learning algorithm is to determine a set of weights w that minimize the total sum of squared errors (E), as shown expression (2):

$$E=\sum_i \left[Y_i-f(w_i,X_i)\right]^2 \tag{2}$$

ANN is widely used for problems associated with data classification because it has high robustness, fault tolerance, and stability in the face of a large volume of data and is recommended for sorting, mathematically modelling, analysing, and interpolating data [23–26].

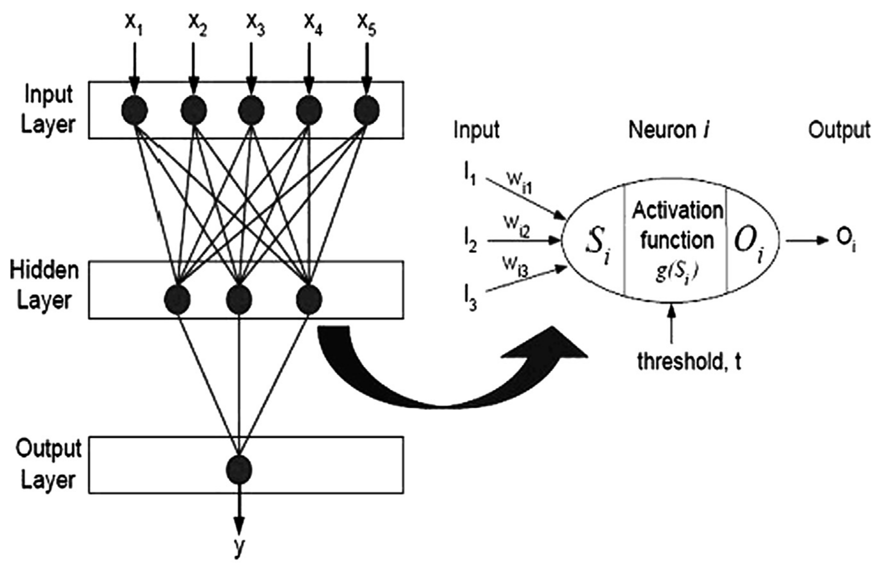

Fig. 2. ANN. basic scheme.

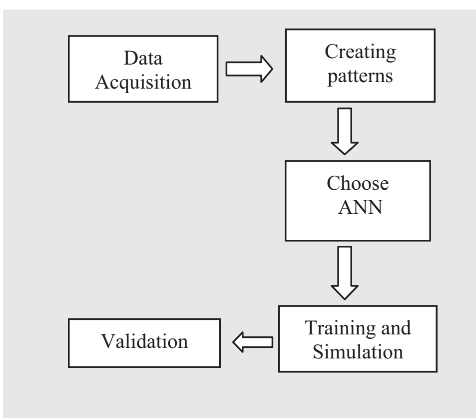

Fig. 3. Classification stages.

4. Classification of load curves

The classification of load curves allows the behaviour of consumers and the electrical system to be identified and analysed, enabling the cost of using the distribution system and network expansion to be calculated. Knowledge of the profile of the load will also anticipate the growth in demand from the existing system (lines and substations) and of new networks with the aim of improving the calculation of sizing systems and optimising the physical and financial planning of its expansion. A lack of knowledge of the profile of each consumer group makes it considerably more difficult to assess the benefits of energy conservation programs. Furthermore, in the short term, managing consumer demand and network demands can generate large cost savings [12,19].

Therefore, the classification of curves is very important in the implementation of DSM policies because it allows the optimisation of system management from the choice of the most appropriate actions for each type of curve load.

Currently, there is no definition on the part of the Brazilian regulator for the methodology of classification of load curves. The traditional practice is the manual selection from the visual analysis of load curves. This analysis is performed with own criteria study group, with possible subjectivities. Some Brazilian energy companies use a commercial software based on the method of dynamic clouds consisting of algorithms that emphasize minimizing internal variance of grouping, maximizing your distance in relation to other groups. This method requires large processing capacity.

The use of ANN for the classification of curves was used in this study because of its characteristics of robustness, efficiency and speed of processing on a large volume of data.

A simulation of the load curve was performed according to the process depicted in Fig. 3. This classification can also be applied to the load curves of feeders or transformers or directly to consumers of the electric system.

The classification of power supplies or transformers from load curves provides an indication of which handlers or processors should have their individual loads studied and controlled for system optimisation. In this paper, we examined the classification of consumer load curves.

4.1. Data acquisition

The input data were provided by a local energy distribution company and obtained from measurements conducted every four years to calculate tariffs. In all, 96 measurements were performed per day for 2000 low-voltage random consumers (residential, commercial and industrial) over one month. The weekend data were considered separately because they differ strongly from the weekday data.

These data were processed to obtain the median curve for five weekdays for each consumer analysed and were normalised to compare the curve shape rather than the absolute consumption.

4.2. Creating patterns

Based on the data obtained in the previous step, it created an array of standardized data and Matlab software was used to simulate the creation of standard curves with different features using the *k*-means method.

The basic idea of the algorithm *k*-means is to group the data around centers named centroids, creating partitions with new classes that cause new partitions, all of this in a cycle that ends only when the partitions cannot be improved or until they reach a predetermined level of precision. The algorithm provides an automatic classification without the need of any human supervision. This method is one of the most used by brasilian energy

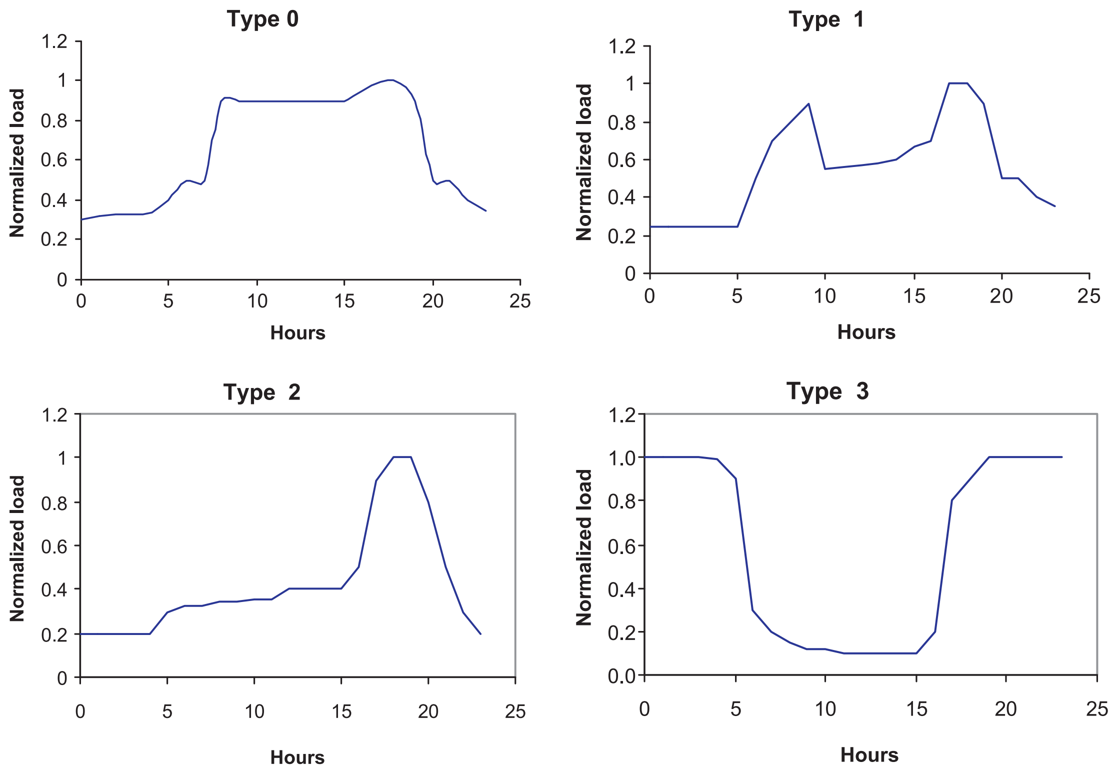

Fig. 4. Load curve patterns.

companies for creating patterns of consumption when they need to calculate the cost of energy.

Four curved patterns were created with different characteristics. It is observed that for these data analysed the four standards are sufficient to define the most appropriate DSM techniques because they have well-defined characteristics for a peak, two or more peaks.

The standards are created to allow the most appropriate policy for DSM to be selected for each type of consumption, e.g., peak shift or control, load control, energy efficiency, or distributed generation. Of course, the choice of the number of standards should consider the needs of the energy company. Fig. 4 shows four load curve patterns with the following characteristics:

– Type 0 presents a fairly constant consumption throughout the day, with a slightly elevated peak-hour consumption. Management actions for this case can be based on energy efficiency and conservation policies, besides the use of distributed generation and differentiated tariff.
– Type 1 shows two more pronounced peaks in consumption, which implies the need for action to control the peak through tariff incentives and direct control load or peak displacement, power generation by the consumer, or accumulation negotiated with the consumer through tariff incentives, depending on the knowledge of the cadastral data of consumers.
– Type 2 shows a sharp consumption peak, implying the need for policies to reduce the peak and fill the valleys, for which direct control and/or distributed generation can be used, besides the use of distributed generation and differentiated tariff.
– Type 3 presents peaks only during the night. This load type is characteristic of LED streetlights. In this case, the actions may involve the replacement of lamps with higher-efficiency ones.

The choice of the number of standards depends on the company's objective with respect to the classification of curves, e.g., for pricing policies for DSM or simply for the planning or operation of the system. Any of these objectives is required for classification and the selection of more appropriate policies for each set of loads with the same characteristics.

4.3. Choise of ANN

The software used for the simulation was the Mathworks Matlab ANN Toolbox, version 7. Feedforward architecture was used with three layers (input, output, and hidden, containing 10, 20, and 1 neuron(s), respectively), and the activation function was the hyperbolic tangent.

Several other architectures with different numbers of neurons per layer were created, but the chosen architecture presented the best performance (minimum error, maximum speed) in the data classification.

4.4. Training and simulation

For training, a set of 100 load curves was chosen at random, including their respective classification (type 0, type 1, type 2, or type 3). Numerous training algorithms were tested, such as backpropagation with and without time; however, the training algorithm that performed best was the learning vector quantisation (LVQ) algorithm [27].

The LVQ algorithm converged to a quadratic error of 10^{-4} at 196 steps, as shown in Fig. 5. This training algorithm showed better performance than the other traditional algorithms tested [21–26].

4.5. Network validation

For method validation, a simulation was performed using 220 different samples of ANN training data. Table 1 presents the error calculated from the difference between the expected value and the estimated value, showing that the maximum error is less than the track between the types. Table 1 also shows the percentage of success in terms of a maximum permissible error of 1%. This

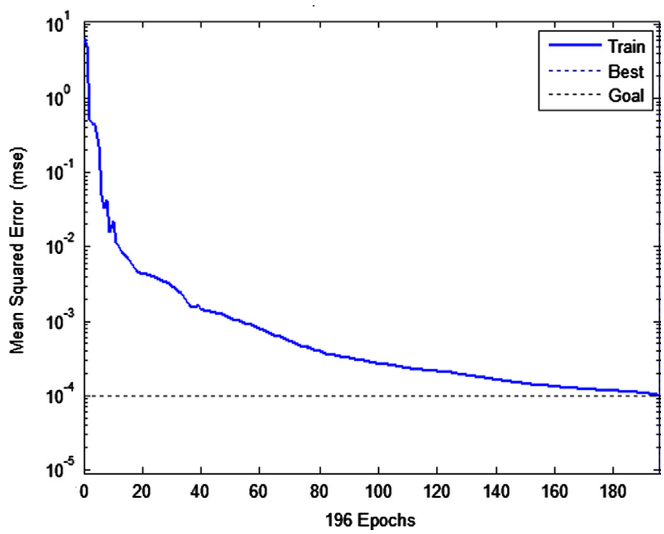

Fig. 5. Training performance.

Table 1
Proposed ANN method error.

Type	Mean error	Maximum error	Success (%)
0	0.0124	0.0353	96.4
1	0.0260	0.0362	94.5
2	0.0179	0.0269	98.2
3	0.0104	0.0153	100

finding confirms that the network has classified the sample accurately.

5. Conclusion

The availability of a large volume of data from the electricity sector in real time due to the new smart grid environment creates promising opportunities for the management of the electrical system. When processed by suitable tools, consumer profile data can be combined with the tools available in the DSM to change consumer habits and provide policy development to optimise the system and make it more efficient and sustainable.

The basic idea is to implement a classification tool for the load curves of all consumers of a power utility in data centres and from various consumer profiles, together with the registration data and analysis of each load feeder, and to use this information to implement policies that optimise the management of the electrical system.

The artificial neural network tool presented a satisfactory performance in rating the load curves in this study. It can be used to obtain more information about the electric process in this new environment, enabling a variety of applications, such as the determination of the most suitable choice of DSM for each type of load, system optimisation, and dynamic pricing based on consumer habits.

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